# Final Report

This report summarizes activities under the Air Force Office of Scientific Research (AFOSR) Grant No. FA9550-07-1-0045 entitled "SECURITY OF COMPLEX NETWORKS." The duration of the project was 1/1/2007-11/30/2009. The report is divided into the following Sections:

1. Objectives
2. List of Publications
3. Accomplishments and New Findings
4. Personnel Supported and Theses Supervised by PI
5. Interactions/Transitions
6. Past Honors

# 1 Objectives

The main goal of the project was to conduct a comprehensive study of complex networks from the perspectives of security and information protection using an interdisciplinary approach. Examples of specific Objectives were

- Cascading breakdown of complex networks triggered by attacks and control strategies;
- Security of complex clustered networks and gradient networks;
- Attack-induced oscillations of complex networks and control strategies;
- Security and robustness of wireless sensor networks;
- Optimization of synchronization in complex networks;
- Dynamics-based network scalability;
- Spreading processes on complex networks;
- Searching for universal dynamics on complex networks;
- Time-series based prediction of hub nodes and network topology.

All Objectives have been completed. A number of discoveries have been made on the fundamental dynamics underlying the security of large complex networks. The AFOSR support has resulted in two dozens of papers published in well recognized journals [e.g., Physical Review E and Physical Review Letters (American Physical Society), Chaos (American Institute of Physics)].

# 2 List of Publications

1. L. Huang, Y.-C. Lai, K. Park, J.-S. Zhang, and Z. Hu, "Critical behavior of blind spots in sensor networks," *Chaos* **17**, 023132(1-8) (2007).
2. L. Zhao, T. H. Cupertino, K. Park, and Y.-C. Lai, "Optimal structure of complex networks for minimizing traffic congestion," *Chaos* **17**, 043103(1-5) (2007).
3. X.-G. Wang, L. Huang, Y.-C. Lai, and C. H. Lai, "Optimization of synchronization in gradient clustered networks," *Physical Review E* **76**, 056113(1-5) (2007).
4. L. Huang, Y.-C. Lai, and R. A. Gatenby, "Optimization of synchronization in complex clustered networks," *Chaos* **18**, 013101(1-10) (2008). [This work was selected by the Virtual Journal of Biological Physics Research for the January 15, 2008 issue (http://www.vjbio.org).]
5. L. Huang, Y.-C. Lai, and R. A. Gatenby, "Alternating synchronizability of complex clustered network with regular local structure," *Physical Review E* **77**, 016103(1-7) (2008). [This work was selected by the Virtual Journal of Biological Physics Research for the January 15, 2008 issue (http://www.vjbio.org).]
6. S.-G. Guan, X.-G. Wang, Y.-C. Lai, and C. H. Lai, "Transition to global synchronization in clustered networks," *Physical Review E* **77**, 046211(1-5) (2008).
7. R. Yang, L. Huang, and Y.-C. Lai, "Selectivity-based spreading dynamics on complex networks," *Physical Review E* **78**, 026111(1-5) (2008).
8. L. Huang, Y.-C. Lai, and G.-R. Chen, "Understanding and preventing cascading breakdown in complex clustered networks," *Physical Review E* **78**, 036116(1-5) (2008).
9. L. Huang, Y.-C. Lai, and R. A. Gatenby, "Dynamics based scalability of complex networks," *Physical Review E (Rapid Communications)* **78**, 045102(1-4) (2008).
10. X.-G. Wang, L. Huang, S.-G. Guan, Y.-C. Lai, and C. H. Lai, "Onset of synchronization in complex gradient networks," *Chaos* **18**, 037117(1-7) (2008).
11. X.-J. Ma, L. Huang, Y.-C. Lai, Y. Wang, and Z.-G. Zheng, "Synchronization-based scalability in complex clustered networks," *Chaos* **18**, 043109(1-9) (2008).

12. R. Yang, T. Zhou, Y.-B. Xie, Y.-C. Lai, and B.-H. Wang, "Optimal contact process on complex networks," *Physical Review E* **78**, 066109(1-5) (2008).

13. R. Yang, W.-X. Wang, Y.-C. Lai, G.-R. Chen, "Optimal weighting scheme for suppressing cascades and traffic congestion in complex networks," *Physical Review E* **79**, 026112(1-6) (2009).

14. W.-X. Wang, L. Huang, Y.-C. Lai, G.-R. Chen, "Onset of synchronization in weighted scale-free networks," *Chaos* **19**, 013134(1-8) (2009).

15. R. Yang, L. Huang, and Y.-C. Lai, "Transient disorder in dynamically growing networks," *Physical Review E* **79**, 046101(1-7) (2009).

16. X.-J. Ma, L. Huang, Y.-C. Lai, and Z.-G. Zheng, "Emergence of loop structure in scale-free networks and dynamical consequences," *Physical Review E* **79**, 056106(1-6) (2009).

17. H.-X. Yang, W.-X. Wang, Z.-X. Wu, Y.-C. Lai, and B.-H. Wang, "Diversity-optimized cooperation on complex networks," *Physical Review E* **79**, 056107(1-7) (2009).

18. W.-X. Wang, Q.-F. Chen, L. Huang, Y.-C. Lai, and M. A. F. Harrison, "Scaling of noisy fluctuations in complex networks and applications to network detection," *Physical Review E* **80**, 016116(1-6) (2009).

19. W.-X. Wang, L. Huang, and Y.-C. Lai, "Universal dynamics in complex networks," *Europhysics Letters* **87**, 18006(1-5) (2009).

20. W.-X. Wang, Z.-X.Wu, R. Jiang, G.-R. Chen, and Y.-C. Lai, "Abrupt transition to complete congestion on complex networks and control," *Chaos* **19**, 033106(1-7) (2009).

21. W.-X. Wang and Y.-C. Lai, "Abnormal cascading on complex networks," *Physical Review E* **80**, 036109(1-6) (2009).

22. X.-G. Wang, S.-G. Guan, Y.-C. Lai, B. Li, and C. H. Lai, "Desynchronization and on-off intermittency in complex networks," *Europhysics Letters* **88**, 28001(1-5) (2009).

23. J. Ren, W.-W. Wang, B. Li, and Y.-C. Lai, "Noise bridges dynamical correlation and topology in coupled oscillator networks," *Physical Review Letters* **104**, 058701(1-4) (2010).

24. H.-J. Shi, R. Yang, W.-X. Wang, and Y.-C. Lai, "Basins of species coexistence and extinction in spatial rock-paper-scissors games," *Physical Review E (Rapid Communications)*, accepted.

25. L.-L. Jiang, W.-X. Wang, Y.-C. Lai, and B.-H. Wang, "Risk-avoidance migration induced cooperation in spatial games," submitted to *Physical Review E* (acceptance expected).

# 3 Accomplishments and New Findings

## 3.1 Cascading Breakdown in Complex Networks and Prevention

Cascading breakdown in complex networks is referred to as an avalanching type of process, where the failure of a single or a few nodes can result in a large-scale breakdown of the network. In particular, in a physical network nodes carry and process certain loads, such as electrical power, and their load-bearing capacities are finite. When a node fails, the load that it carries will be redistributed to other nodes, potentially triggering more failures in the network as a result of overloading. This process can propagate through the entire network, leading to its breakdown. Indeed, cascading breakdown appears to be particularly relevant for large-scale failures of electrical power grids, and efforts have been made to understand the dynamical origin of such failures. The study of cascading breakdown began in 2002, where the ASU group was among the first to recognize the potential impact of this type of dynamics on the security of large complex networks.

During the project period, the ASU group furthered the study on cascading dynamics and addressed a number of problems. In addition to obtaining fundamental understanding of cascading dynamics, the group focused on exploring methods to control, mitigate, and prevent this type of catastrophic dynamics. Specific problems investigated include (1) understanding and preventing cascading breakdown in complex clustered networks, (2) optimal weighting scheme for suppressing cascades and traffic congestion in complex networks, (3) abnormal cascading on complex networks, (4) optimal structure of complex networks for minimizing traffic congestion, and (5) abrupt transition to complete congestion on complex networks and control.

For example, in one work (paper #8 in the publication list), we addressed the dynamical origin of cascading processes on complex *clustered* networks and, more importantly, investigated how such a network can be made secure in response to attacks. In view of the particular vulnerability of scale-free networks to cascading breakdown, we focused on networks where each individual cluster contains a scale-free subnetwork. The challenges can be illuminated by considering the problem of virus spread starting from one of the clusters, such as a remote village in a human epidemic network. A common practice to prevent a global spread is to isolate this particular cluster from the network. Now, consider the network-security problem by assuming that an attack has occurred in one of the clusters. A naive strategy to prevent breakdown of the network on a global scale is to isolate this cluster by cutting all the links that connect this cluster with other clusters so that failures would be restricted to the original cluster. This intuitive thinking, however, cannot be correct for a load-distributed network, because cutting off a cluster would transfer the load originally processed by this cluster to other clusters of the network, increasing the likelihood of overloading and possibly resulting in a more disastrous situation. Indeed, this is what we found in simulations: a clustered network is particularly vulnerable to cascading breakdown in the sense that the prevention strategy based on intentional, pre-emptive removal of a set of selective nodes from the network, which is quite effective for scale-free networks, would increase significantly the probability of a global avalanche if not properly implemented. To overcome the difficulties, we developed the idea of classifying and understanding the roles played by various nodes in the network and devise a control strategy accordingly that can effectively prevent global cascades. Our achievement is illustrated in Fig. 1, plots of the relative size $G$ of the largest connected component of the network versus some generic network capacity parameter $\lambda$ in response to an attack on a hub node, where $G = 1$ represents a fully connected network and $G \ll 1$ indicates that the network has disintegrated effectively. The data points represented by open squares correspond to the situation where no control is taken to protect the network, and those represented by open circles are the result of cutting off the particular cluster within which the attack occurs. We observe that, as $\lambda$ is reduced, $G$ decreases rapidly but strikingly, there is essentially no difference in the values of $G$ between these two cases, indicating the ineffectiveness of an straightforward implementation of the prevention strategy which tries to localize the destruction within one community. In contrast, implementing our control strategy results in much higher values of $G$ (data points represented by open triangles).

In another work (paper #21 in the publication list), we revisited the concepts and definitions of load and capacity, which are fundamental to dynamical processes on complex networks, especially to those related to security. This was motivated by the fact that the extremely commonly used definition of load in the complex-network literature, namely, betweenness, may not be physically realistic in situations that concern network security. In particular, betweenness is based on the consideration that information is transmitted along the various shortest paths, e.g., as in a computer network. Assume that, in each time unit, a node transfers one data packet along any shortest path through the node. The total number of packets that the node handles in one time unit is thus equal to the number of shortest paths through it, so the betweenness represents the load. The node capacity can then be defined as being proportional to the initial load. However, such a definition of load and node capacity may be too idealized for realistic network systems supporting a variety of flows. We were thus interested in alternative ways to define node capacity for the study of cascading dynamics on networks. Moreover, in physical, chemical, and biological networks the quantities of interest are usually variables such as the electrical currents or chemical concentrations. In such a case the underlying rules governing the evolutions of the relevant variables are a significantly more important factor to determine the flow than merely the number of shortest paths (betweenness). We suggested to define load and capacity based on laws governing physical flows on the network. To be as general as possible, we studied weighted complex networks to take into account heterogeneous node-to-node

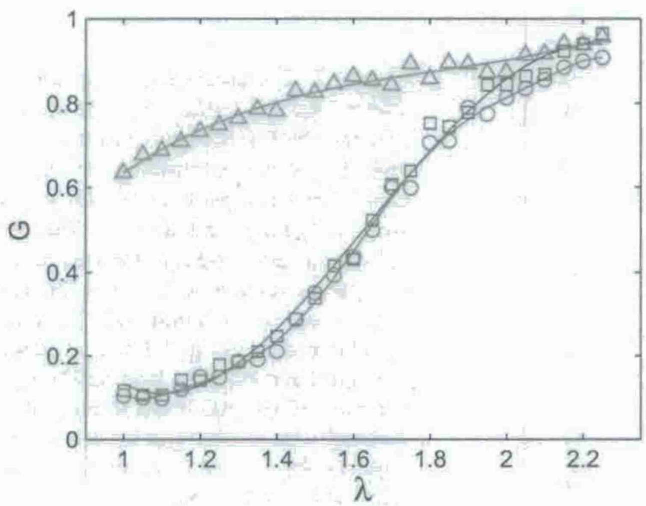


Figure 1: For a representative clustered network of $N = 5600$ nodes, average degree $\langle k \rangle = 4$, $M = 50$ clusters, and average inter-cluster number of links $k_M = 2$, the relative size $G$ of the largest connected component in the network versus the network capacity parameter $\lambda$ in response to a targeted attack. Each data point is the result of averaging 100 network realizations (see text for details of the meanings of the three different data curves). The attack disables a single node in a cluster that has the largest load. For a non-clustered scale-free network, the value of $G$ can be about zero for $\lambda \simeq 1$. However, for a clustered network, failures propagate from one cluster to another, during which a few connected clusters may be separated from the rest but still remain connected. As a result, the value of $G$ for small values of $\lambda$ is small but not zero; it is of the order of $1/M$.

interactions. Our main finding was that heterogeneous flow distribution at nodes can significantly enhance the network's ability to counter cascading failures as triggered by intentional attacks. This is surprising, considering that heterogeneous networks being more vulnerable to cascading failures is a central result from models in the complex-network literature that use betweenness to define load. We also found that, incorporating inherent edge capacity on the network, situations can arise where a quantity characterizing the degree of the cascading failure can exhibit a non-monotonic behavior as a function of the capacity parameter. This implies that, for a given network setting, there can be an interval in the capacity parameter where enhancing it can actually cause the network to be more vulnerable to cascading failures. While our findings were counterintuitive with respect to previous results, we provided analyses and numerical computations to establish that they are the consequences of considering flow and capacity in a more realistic way, and these phenomena are expected to be generic for real-world complex networks.

We also worked out a strategy to control cascading dynamics and to mitigate traffic congestion on complex networks (paper #13 in the publication list). A previous method was based on the idea to remove a set of "insignificant" nodes that contribute more load to the network than they handle so as to enhance the overall load-handling capability of the network. This strategy may be regarded as "hard" because it requires that certain nodes be removed from the network, which leads to structural changes in the network. An issue of interest was whether some proper "soft" control strategy can be developed to prevent cascading breakdown but to keep the connections among nodes unchanged. Motivated by this consideration, we articulated a a general "soft" control strategy to prevent cascading breakdown and catastrophic traffic congestion on complex networks. Our main idea was based on the following two facts: (1) in real-world networks the node capacity is not linearly proportional to the load, and (2) transmission paths can be adjusted by arbitrarily given link weights. In a complex network, links to and from hub nodes tend to be used more frequently than other links in the network. The weight of a link can thus be assumed to depend on the degrees of the two nodes that it connects so that loads through links and nodes can be tuned by weights. Consequently, information flows on the network depend on the weights. We found that there exists an optimal weighting scheme for which cascading failures and traffic congestion can be suppressed significantly. In particular, the robustness of a network against cascading failures is characterized by the critical values of a pair of tolerance parameters, at which there exists a phase transition from an absorbing (free) state to a cascading state. The critical values can be regarded, qualitatively, as corresponding to the minimum cost for protecting networks to avoid cascading damages. The optimal weighting scheme can thus be quantified by the lowest minimum cost. For traffic flow dynamics, the network throughput is characterized by the maximum packet

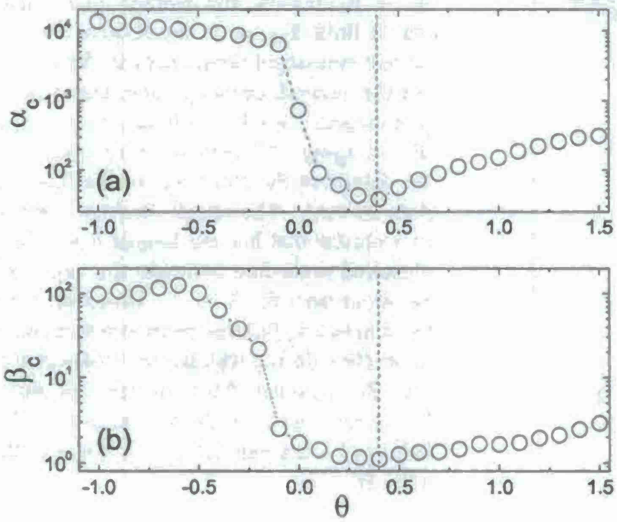


Figure 2: For model scale-free networks whose load and traffic dynamics are characterized by two robustness parameters $\alpha_c$ and $\beta_c$ (or phase-transition points), the change of these parameters with the network weighting parameter $\theta$. The vertical dashed lines indicate the existence of an optimal value $\theta = \bar{\theta} \approx 0.4$ for which both $\alpha_c$ and $\beta_c$ are minimized. The results are obtained by using 100 runs of network dynamics according to load redistribution for each of the 100 network realizations. Network size is 1000 and the minimum of degree is $k_{min} = 10$. See paper #13 in the publication list for details.

generation rate for which the network is free of congestion. The higher the maximum generation rate, the more efficient network traffic can be. What we found through heuristic analysis and numerical computations on both model and real-world networks was that under the optimal weighting scheme, the lowest minimum protection cost and the highest packet generation rate can be achieved simultaneously and, quite strikingly, the minimum cost can be several orders of magnitude smaller than the values realized in the underlying non-weighted network, as exemplified by simulation results from a model scale-free network in Fig. 2. For real-world networks such as the power grid and the internet, we found similar behaviors. In a practical sense, this means that the network can essentially be cascade- and congestion-free through the control implementation of some appropriate weighting scheme.

### 3.2 Synchronization in Complex Networks

The complex-network approach has recently been used widely to investigate and understand the dynamics and statistical properties of multi-component systems, such as neuron systems and computer networks. Synchronization is one of the fundamental properties characterizing collective motions of complex systems with many interacting components. The ASU group was among the pioneers to address the problem of synchronization in complex networks. In a work published in 2003 (sponsored by a previous AFOSR MURI project), the group reported the first study of synchronization in scale-free networks [T. Nishikawa, A. E. Motter, Y.-C. Lai, and F. Hoppensteadt, "Heterogeneity in oscillator networks: Are smaller worlds easier to synchronize?" *Physical Review Letters* **91**, 014101(1-4) (2003)]. The work has received about 300 citations at the writing of this Report.

During the project period, the ASU group pioneered the study of synchronization in complex *clustered* networks. In particular, in the past several years, the importance of complex clustered topology has been recognized, especially in biological, social, and certain technological networks. Such a network can be represented by a collection of sparsely linked clusters of nodes, where the connectivity within any individual cluster is dense. Examples of complex clustered networks include certain computer networks, many social networks, and biological networks such as protein-protein interaction networks and metabolic graphs. The ASU group obtained a number of results on the fundamental dynamics of synchronization in complex *clustered* networks.

For example, in one work (paper #4 in the publication list), we addressed the following basic question:

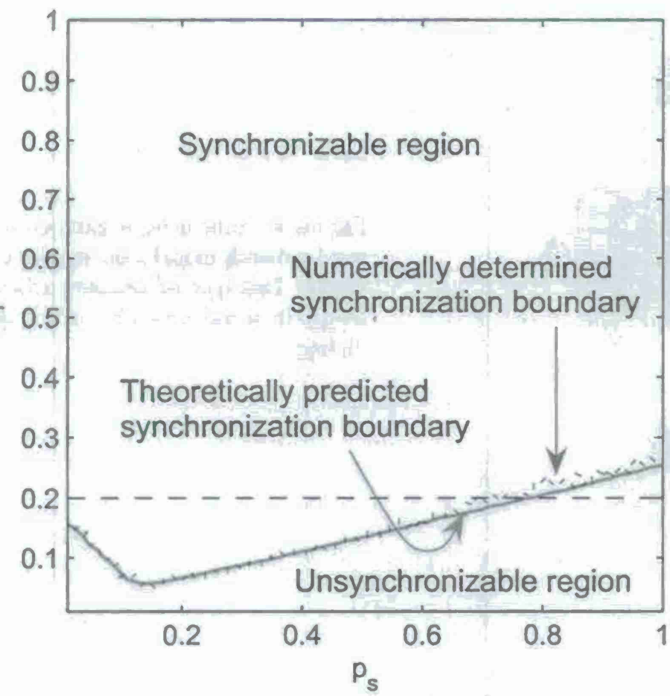


Figure 3: For a complex clustered network whose dynamics are described by $d\mathbf{x}_i/dt = \mathbf{F}(\mathbf{x}_i) - \epsilon \sum_{j=1}^{N} G_{ij}\mathbf{H}(\mathbf{x}_j)$, where $\mathbf{F}(\mathbf{x}) = [-(y+z), x+0.2y, 0.2+z(x-9)]^T$ (Rössler chaotic oscillator), $\mathbf{H}(\mathbf{x}) = [x, 0, 0]^T$ is a linear coupling function, $\epsilon$ is global coupling parameter, and $\mathbf{G}$ is the coupling matrix describing the network topology, synchronization boundary in the two-dimensional parameter space of the frequencies of intra-cluster and inter-cluster links. The dotted line is the obtained from direct simulation of the network synchronization dynamics, and the solid line is from theoretical analysis. The network contains 100 nodes and 2 distinct clusters. The coupling parameter is $\epsilon = 0.5$. Each data point is the result of averaging over 1000 network realizations.

under what condition can the synchronizability of a complex clustered network be optimized? To address this question, the ASU group recognized the two basic parameters characterizing a complex clustered network: the probabilities of inter-cluster and intra-cluster connections. It is thus insightful to investigate, in the corresponding two-dimensional parameter plane, regions where the network can be best synchronized. A representative example is shown in Fig. 3. Our study yielded a quite surprising finding: a complex clustered network is most synchronizable when the two probabilities match each other approximately. Mismatch, for instance caused by an overwhelming increase in the number of intra-cluster links, can counterintuitively suppress or even destroy synchronization, even though such an increase tends to reduce the average network distance. This suggests that, to achieve robust synchronization in a complex clustered network, simply counting the number of links is not adequate. Instead, links should be classified carefully and placed properly between or within the clusters to optimize possible synchronization-related functions of the network. The potential significance of this result can be illustrated by a specific example: efficient computation on a computer network. Suppose a large-scale, parallel computational task is to be accomplished by the network, for which synchronous timing is of paramount importance. Our result can provide useful clues as to how to design the network to achieve the best possible synchronization and consequently optimal computational efficiency.

In another work (paper #5 in the publication list), we investigated the synchronizability of locally regular, complex clustered networks. A schematic illustration of this type of networks is shown in Fig. 4, which are typical of social networks and also arise commonly in systems biology. Since our works on the synchronizability of clustered networks revealed that more links, which make the network smaller, do not necessarily lead to a stronger synchronizability and since the globally random connections among clusters are usually sparse, a key question was then what can happen to network synchronizability when the density of intra-cluster links is varied. We found that, for a typical locally regular clustered network, its synchronizability exhibits an alternating, highly non-monotonic behavior as a function of the intra-cluster link density. In fact, there are distinct regions of the density for which the network synchronizability is maximized, but there are also parameter regions in between for which the synchronizability diminishes. We showed that, while surprising, this phenomenon of *alternating synchronizability* can be fully explained theoretically based on analyzing the behavior of the eigenvalues and

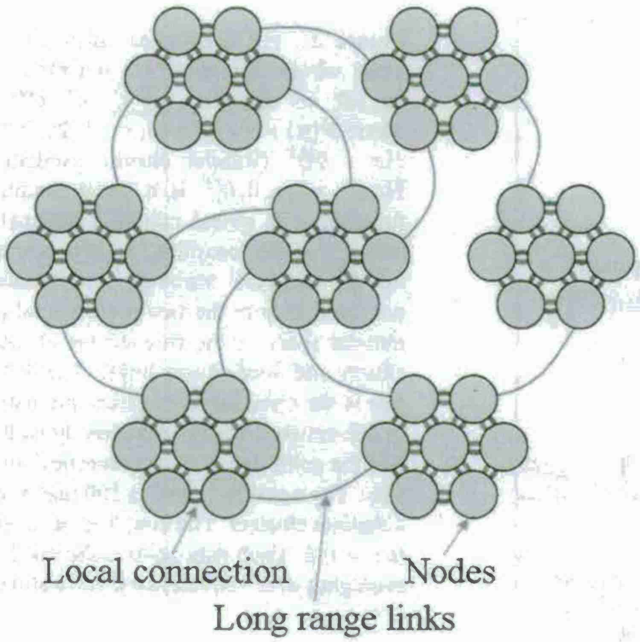


Figure 4: Schematic illustration of clustered network model with regular subnetworks. This type of structure arises commonly in social networks and in systems biology.

eigenvectors of the coupling matrix. A feature that made our theoretical analysis feasible is that, due to the locally regular topology of the network, some key eigenvectors within each individual cluster exhibit periodic wave patterns. Both numerical eigenvalue calculations and direct simulation of the actual synchronization dynamics of the underlying oscillator network provided firm support for the theory. One implication is that, in order to achieve robust synchronization, the density of the local connections within a cluster needs to be appropriately tuned since both high density and low density can hinder synchronization.

We also investigated dynamical scalability in complex networks (paper #9 in publication list), an important issue in many branches of science and engineering that involve networks of varying sizes. For example, in biology, synchronization can occur in systems of different sizes, ranging from neuronal and cellular networks to population dynamics in natural habitats of vast distances. In computer science, whether a particular program can work in systems containing orders-of-magnitude different numbers of components is always a pressing issue. Similar scalability issues arise in large-scale circuit designs. Our interest was in *dynamics-based scalability* of complex networks. In particular, we asked, if a dynamical phenomenon of interest occurs in networks of size $N_1$, can the same phenomenon be anticipated in networks of size $N_2$, where $N_2$ is substantially larger than $N_1$? More importantly, does the scalability so defined depend on the network topology? To be concrete, we focused on the synchronization dynamics and studied the interplay between synchronization-based scalability and network topology. The distinct type of network topologies included in our pursuit were globally connected, locally coupled regular, random and scale-free. Our main finding was that globally coupled networks and random networks are scalable, but locally coupled regular networks are not. Scale-free networks are scalable for certain types of node dynamics. These results can provide insights into some fundamental issues in sciences and engineering. For example, large scale-free networks can be unsynchronizable and, hence, the scale-free topology may not be important, or less ubiquitous, in situations where synchronization is key to system functions. From the standpoint of network design to achieve some desired synchronization-dependent performance, random networks are more advantageous.

### 3.3 Universal Dynamics in Complex Networks

Universality is one of the most fundamental issues in physical sciences and engineeirng. Critical phenomena and universal scaling laws associated with phase transitions in a large variety of non-equilibrial physical and chemical systems and universal routes to chaos in nonlinear dynamical systems are classical examples. Searching for universality is thus one of the most pursued endeavors in science. In view of the tremendous amount of interest in complex networks, we asked whether there exist *universal dynamics* on these networks. In particular, given networks from different contexts, is there a universal class of dynamics that absolutely has no dependence on structural details of the network?

In the project period, we uncovered a class of universal dynamics on weighted complex networks (papers #10 and #19 in the publication list). In particular, we found the existence of weighting schemes for which the details of various real-world networks, whether biological, technological, or social, have little influence on typical dynamical processes such as synchronization, epidemic spreading, and percolation. Here, in our computation, we used the topologies of a number of real-world networks from different disciplines and imposed a controllable weighting schemes to model the coupling configuration of the network. In other words, by incorporating our proposed weighting scheme into any complex networks, the networks exhibit universal dynamics, regardless of their difference in topology. This striking universality in network dynamics was demonstrated by using a large number of real-world networks and substantiated by analytic considerations. The universality makes possible generic and robust control strategies for a variety of dynamical processes on networks arising from different contexts.

The key to our success in searching for universal network dynamics lay in considering weights on networks. Indeed, in real-world networks, interactions among nodes are not uniform but typically are heterogeneous, or weighted. To be general, we examined both symmetric and asymmetric weighting schemes. To be able to carry out concrete and quantitative analysis to cover as many types of network dynamics as possible, we chose to examine the behavior of the largest eigenvalue of the weighted adjacency matrix, denoted by $\lambda_N$. The role of $\lambda_N$ in different types of dynamics can be appreciated through the following examples: in a heterogeneous dynamical network, $\lambda_N$ determines the emergence of coherence; in epidemic spreading, $\lambda_N$ sets the infection threshold for outbreak of virus and shapes the onset of percolation transition; in general, $\lambda_N$ governs the linear stability of system of coupled dynamical elements. Our approach was to explore the dependence of $\lambda_N$ on some parameters, say $\alpha$, that characterizes the weighting scheme.

We studied twelve different realistic networks ranging from the neural network of C. Elegans in biology to the Internet at the level of autonomous systems and to social networks such as the American football games. Results are presented in Fig. 5. In particular, the figure shows, for symmetric weighted complex networks, the largest eigenvalue $\lambda_N$ of the weighted adjacency matrix as a function of the weighting parameter $\alpha$. The networks are: (1) the neural network of C. Elegans (denoted by C. E), (2) transcriptional regulation network of E. coli (E. C), (3) protein-protein interaction network of yeast (PPI), (4) electronic circuit network (EC), (5) the Internet at the level of autonomous systems (IAS), (6) Western States Power Grid of the United States (PG), (7) dolphin social network (DS), (8) network of American football games among colleges (AFC), (9) social network of friendships of a karate club (FKC), (10) network of political book purchases (PBP), (11) high-energy theory collaboration network (HTC), and (12) collaboration network of scientists working on network theory and experiment (NSC). Note that examples (1-3) belong to biological networks, (4-6) are physical and technological networks, and (7-12) are social networks. Intuitively, for any two different types of networks, the $\lambda_N$-$\alpha$ curves are expected to be distinct and generically to intersect at some value, say $\alpha_c$. The striking finding is that all the $\lambda_N$-$\alpha$ curves from the twelve completely different networks intersect exactly at the same $\alpha_c$! The critical values of $\alpha_c$ and $\lambda_N$ at the intersection point depend only on the weighting scheme and they do not depend on the topological details of the network. This means that, at the intersection point, the specific structural details of different networks disappear and the network dynamics become universal. To place our finding on a firm ground, we developed an analytic theory for determining the critical values, with predictions agreed well by numerical results. To provide

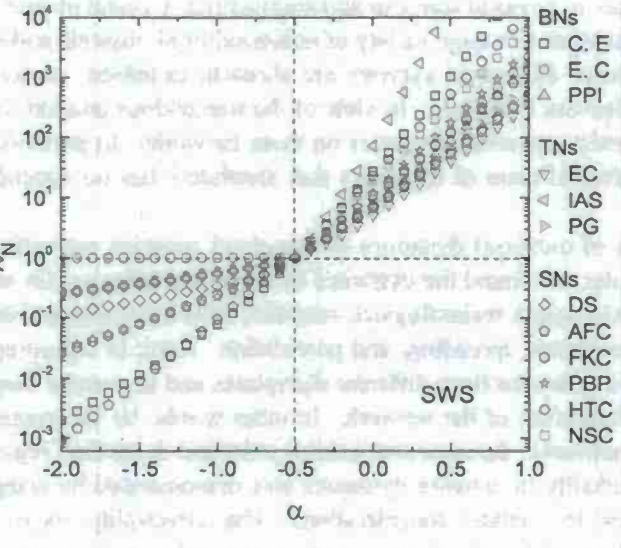


Figure 5: For symmetric weighted complex networks, the largest eigenvalue $\lambda_N$ of the weighted adjacency matrix as a function of the weighting parameter $\alpha$ for twelve different real-world networks. Dashed lines indicate the place where universal critical dynamics arise: $\alpha_c = -0.5$ and $\lambda_N(\alpha_c) = 1$. Similar results were observed for asymmetrically weighted complex networks.

*direct* evidence for the universal dynamics with respect to *actual* dynamical processes, we obtained results from transition to synchronization in the Kuramoto-type of phase coupled dynamics on weighted scale-free networks.

The universal behavior in the collective network dynamics has important implications in significant areas of network research such as the security of complex networks. Say we wish to design a class of networks that are robust to external perturbations. Properly weighted networks provides a solution, as the associated network dynamics are invariant with respect to any structural changes that may be caused by attacks or random failures. Our finding can also be useful for addressing the issue of network scalability, where design principles for networks of significantly different sizes but with identical dynamics are sought.

### 3.4 Spreading Dynamics on Complex Networks

Spreading dynamics on complex networks are fundamental to many branches of science and engineering. In computer science, the propagation and spreading of a virus over the internet have always been of great concern. In biomedical sciences and engineering, the transmission of electrical signals over a neuronal network is critical to its function. In epidemiology, to understand the spreading dynamics of infections on networks is a basic task. Propagation of information over a friendship network is even relevant to political science. Because of the importance of spreading dynamics, it has been under extensive investigation since the beginning of modern network science.

In most existing studies of spreading dynamics on complex networks, the underlying contact process was assumed to be completely random, or non-selective. That is, when a node becomes infected, it selects randomly one of its neighbors and infects it with certain probability. (Here, neighboring nodes are referred to as the set of all nodes in the network that are connected to the original node.) There are, however, many realistic situations where the selection of a target node by an already infected node from its neighbors is not completely random but highly preferential. For instance, in a communication network with a hierarchical structure, once a node in a certain level acquires a piece of information, it is more likely for the information to be sent to some nodes in a higher level. This preferential selection of target node is only one aspect of spreading dynamics. Another equally important ingredient is the selection of an infected node by a susceptible node that has yet to be infected. For example, in a scientific citation network, the better known a paper, the higher the probability that this work

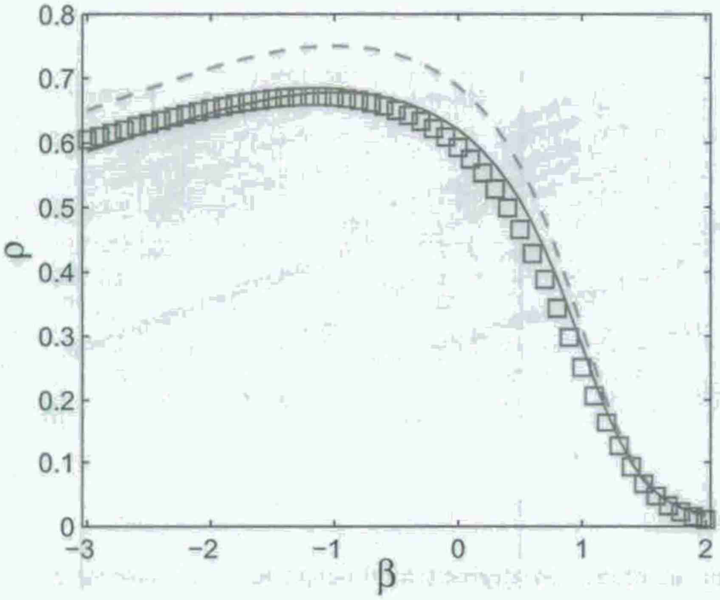


Figure 6: For a representative scale-free network, for $\alpha = 0$, steady-state value $\rho$ of the fraction of infected nodes versus the selection-weighting parameter $\beta$ (for $p = 0.2$). The solid curve is our theoretical prediction. Dashed curve represents the mean-field prediction. Open squares are data points from direct numerical simulations. For each value of $\beta$, the spreading process is evolved for sufficiently long time where $\rho(t)$ becomes nearly a constant (with small and time-independent fluctuations), indicating a steady state. Then $\rho$ is taken as the average of $\rho(t)$ from the last 1000 time steps. An additional average over 100 network realizations is taken in the calculation of $\rho$.

would be cited. This is basically a preferential recognizing (spreading) mechanism. Another example occurs in friendship networks where an individual is more likely to seek and accept his/her best friends' opinions. Such a phenomenon indeed appears to be common in human-relation networks. To better understand spreading dynamics in real-world networks, the preferential selections of a target node by an infected node to pass on the infection and of an infected node by a susceptible node to receive infection must be taken into account.

During the project period, we investigated spreading dynamics with preferential selections (papers #7 and #12 in the publication list). We introduced suitable parameters to characterize the probabilities of the selections. We then considered a generic contact-process (CP) model and obtained analytic results for a fundamental quantity in any spreading dynamics: the fraction of nodes in the entire network that can be infected. Our theory predicted a surprising phenomenon: preferential selections in fact tend to hinder effective spreading. That is, in order to achieve efficient spreading so as to make the fraction of infected nodes as large as possible, both processes of selection should be made as uniform as possible, regardless of the degrees of the nodes. This is somewhat counterintuitive as many previous works emphasized the role of hub nodes, nodes of unusually high degrees, in the spreading dynamics.

Heuristically, this contradiction can be understood, as follows. When the overall fraction of infected nodes is small, preference to select hub nodes helps the infection to survive and to spread by maintaining the hub nodes in a state with a high infection probability, leading to an increased density of infected nodes. However, when the fraction of infected nodes is large, the hub nodes are almost always infected. Thus new attempts for the infection to be sent to the hubs are in fact wasted. In this case, infecting small-degree nodes that have lower probabilities of being infected can be more effective for increasing the overall fraction of infected nodes. From a different perspective, preferential selections tend to suppress the spreading dynamics if the infection or the virus is undesirable, and our theory provided specific scenarios for how selections should be done to achieve this goal. Our theoretical predictions were verified by extensive numerical simulations on scale-free networks.

A technical contribution of our work was the development of a set of new rate equations for spreading dynamics on networks of arbitrary topology. We obtained evidence that our approach yields results that agree with those from numerical experiments more accurately than the predictions from the standard mean-field approach, as exemplified by Fig. 6. Our approach is thus appealing to the study of network spreading dynamics, since the applicability of the mean-field theory to highly heterogeneous networks has been an issue of debate.

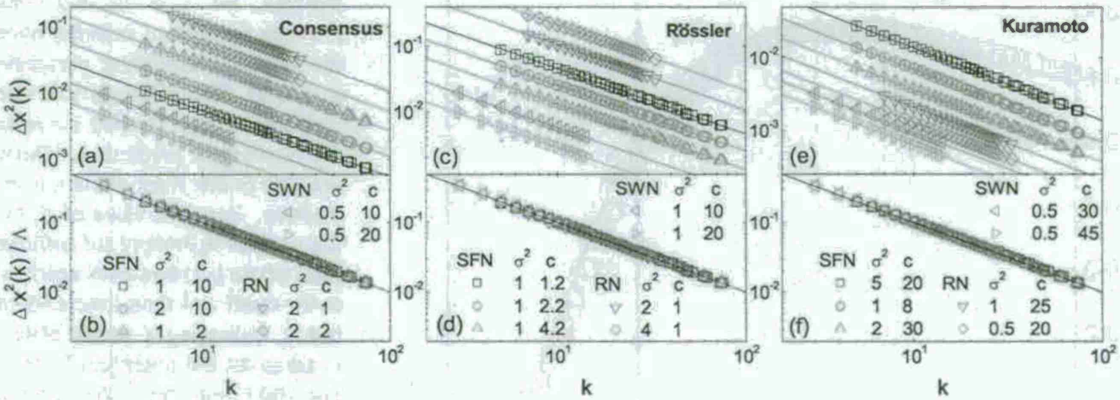


Figure 7: Average fluctuation $\Delta x^2(k)$ as a function of the node degree $k$ for different values of noise variance $\sigma^2$ and coupling strength $c$ on scale-free, random and small-world networks for (a) consensus dynamics, (c) Rössler dynamics, and (e) Kuramoto dynamics. (b,d,f) Rescaled quantity $\Delta x^2(k)/\Lambda$, where $\Lambda = \sigma^2(1 + 1/\langle k \rangle)/(2c)$, versus $k$ for consensus, Rössler and Kuramoto dynamics, respectively. Data points are from a single network configuration and $\Delta x^2(k)$ is obtained by averaging over all nodes of degree $k$ with error bars. The parallel lines in (a), (c) and (e) are theoretical predictions, and the lines in (b), (d) and (f) are the function $1/k$. Network size is 500. For the scale-free network, the lowest degree is $k_{\min} = 5$. For the random network, the connection probability among nodes is 0.03. For the small-world network, the average degree is 8 and the rewiring probability is 0.1. The natural frequency $\omega_i$ in the Kuramoto model is chosen independently from a prescribed probability distribution $g(\omega) = 3/4(1 - \omega^2)$ for $|\omega| \leq 1$ and $g(\omega) = 0$ otherwise.

### 3.5 Predicting Complex Networks from Time Series

Understanding the relationship between dynamics and network structure is a central issue in interdisciplinary science. Despite the tremendous efforts in revealing the topological effect on a variety of dynamics, how to infer the interaction pattern from dynamical behaviors is still challenging as an inverse problem, especially in the absence of the knowledge of nodal dynamics. Some methods aiming to address the inverse problem have been proposed, such as spike classification methods for measuring interactions among neurons from spike trains, and approaches based on response dynamics and $L1$. For the inverse problem, a basic question is whether sufficient topological information can be obtained from measured time series of dynamics. In this regard, the answer is negative when there is strong synchronization as, in this case, the coupled units behave as a single oscillator and interactions among units vanish so that it is impossible to extract the interaction pattern from measurements.

We were interested in the dynamics of large complex networks *in the presence of noise* (paper #18 in the publication list). Despite tremendous recent efforts on complex-network dynamics, the issue of noise has been somewhat overlooked. The presence of noise is, however, ubiquitous in realistic physical and other natural systems. Since a networked system consists of a large number of oscillatory units interacting with each other in a complicated manner, it is meaningful to define, for any given time, a mean field $\langle x \rangle_E$ based on some dynamical variable of interest, say $x(t)$, where $\langle \cdot \rangle_E$ stands for "space" average over the network elements. For node $i$, because of the dynamical evolution under noise, in time its corresponding dynamical variable will fluctuate about the mean field. The average fluctuation over a long observational time interval can then be defined: $\Delta x_j^2 \equiv$

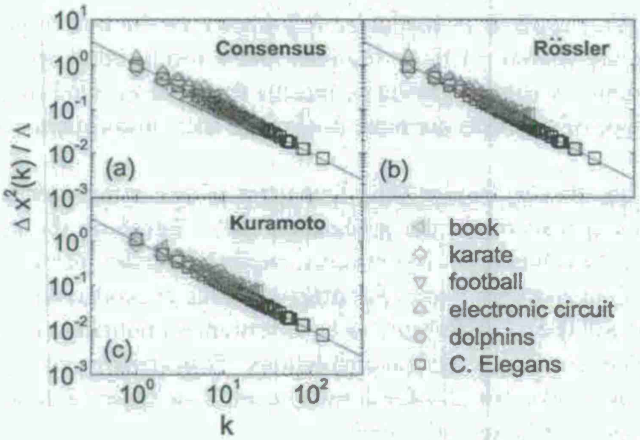


Figure 8: For Universal scaling law for six real-world networks.

$\langle (x_j(t) - \langle x \rangle_E)^2 \rangle_T$, where $\langle \cdot \rangle_T$ denotes the time average. We found that this time-averaged fluctuation scales with the degree $k_j$ (the number of links) of the node as

$$\Delta x_j^2 \sim k_j^{-1}.$$

We argued theoretically and verified numerically that this scaling law holds for a variety of network topologies and node dynamics, as shown in Fig. 7 and 8. An application of our finding is that, since $\Delta x_j^2$ can be calculated purely and efficiently from time series and because of the one-to-one correspondence between $\Delta x_j^2$ and the node degree, the scaling law provides an efficient way to predict the node degrees and consequently hub nodes from network whose detailed topology and node dynamics are not known. Thus, our result, besides being fundamental to nonlinear physics, also addresses a pressing issue of significant practical interest: network prediction based on time series.

Quite recently, we found that, with the help of noise, in general it becomes possible to precisely identify interactions based solely on the correlations among measured time series of nodes (paper #23 in the publication list). In this sense, it can be said that *noise bridges dynamics and topology*, facilitating inference of network structures. In particular, we developed a general and powerful method to precisely identify links among nodes based on the noise-induced relationship between dynamical correlation and topology. By defining the dynamical correlation between pairwise oscillators as the product of their state differences from the averaged values, we obtained a dynamical correlation matrix that can be calculated readily from time series. Analytically, we find that there exists a one-to-one correspondence between the correlation matrix and the connection matrix, due to the presence of noise. This finding enables an accurate prediction of network topology from time series. Numerical simulations were performed using four typical dynamical systems, together with several model and real networks. For all cases examined, comparisons between the original and the predicted topology yielded uniformly high success rate of prediction. The advantages of our noise-based method are then: (i) high accuracy and efficiency, (ii) generality with respect to node dynamics and network structures, (iii) no need for control, and (iv) applicability even when there is weak coherence in the collective dynamics.

### 3.6 Blind Spots in Wireless Sensor Networks

Recent years have witnessed an increasing use of sensor networks in a wide range of applications. Examples include monitoring and collection of information on objects ranging from plankton colonies, endangered species, soil and air contaminants to traffic flow, biomedical subjects, building and bridges, etc.. Sensor networks also find critical applications in homeland defense such as detection of chemical or biological agents and pattern recognition. In a sensor network, the issue of blind spots is of particular importance as the power supplies maintaining the normal operation of the sensors are usually of finite lifetime. As a result, blind spots, i.e., isolated nodes or isolated clusters of nodes, can occur. A central question concerns the onset of blind spots and its dependence on network topologies, i.e., what type of networks are more resilient or more susceptible to blind spots?

During the project period, we addressed this question by investigating four types of sensor network topologies: regular, random, mixed, and heterogeneous (paper #1 in the publication list). Based on the degree-distributions of these networks, we obtained, for the first three types of networks, explicit formulas for the critical value of the occupying probability, below which blind spots are likely. For heterogeneous networks, we derived a computational procedure that allows the critical occupying probability to be determined implicitly. Excellent agreement was found between the theoretical predictions and numerical simulations. These results are expected to be useful not only for designing specific sensor networks, but also for deriving control strategies to restore the networks from catastrophic events as in the aftermath of a large-scale attack.

# 4 Personnel Supported and Theses Supervised by PI

## 4.1 Personnel Supported

The following people received salaries from the AFOSR Project during various time periods.

- **Faculty (partial summer salary):**
  Ying-Cheng Lai (PI), Professor of Electrical Engineering, Professor of Physics

- **Post-Doctoral Fellows (full-time or part-time appointments)**

1. Kwangho Park (1/1/06-12/31/07)
2. Wenxu Wang (3/1/08 - present)
3. Liang Huang (11/1/08-present)

- **Graduate Students**

1. Liang Huang, Ph.D. student in Electrical Engineering
2. Ryan Yang, Ph.D. student in Electrical Engineering

## 4.2 Theses supervised by PI in the project area

1. Liang Huang, Ph.D. in Electrical Engineering, ASU, December 2008; *Dynamics and security of complex clustered network systems* (received the Palais' Outstanding Doctoral Student award for 2008-2009, ASU).

# 5 Interactions/Transitions

Collaboration with AFRL scientists:

- Dr. Vassilios Kovanis, AFRL at Wright Patterson AFB, on *compressive sensing and complex dynamical systems*.

Invited talks on topics derived from the project

1. "Complex networks and applications," Colloquium, Department of Speech and Hearing SCience, ASU; February 21, 2007.

2. "Optimization of synchronization in complex networks," invited plenary talk, 3rd International Conference on Nonlinear Science, Shanghai, China; June 9, 2007.
3. "Optimization of synchronization in complex networks," Special Seminar, College of Physical Sciences, King's College, University of Aberdeen, Scotland; March 12, 2008.
4. "Synchronization in complex networks," Invited talk, Dynamical Systems in Biology - Conference celebrating Prof. Frank Hoppensteadt's 70th birthday, New York University, New York; April 13, 2008.
5. "Probing complex networks from time series," Invited program-review talk, West Virginia High Technology Consortium Foundation, Fairmont, West Virginia; July 17, 2008.
6. "Probing complex networks from time series," Seminar, Department of Electrical Engineering and Computer Science, University of Central Florida, Orlando, Florida; July 25, 2008.
7. "Security of complex networks," Colloquium, Department of Physics and Astronomy, Georgia State University, Atlanta, Georgia; April 14, 2009.
8. "Control of complex networks," Seminar, School of Natural and Computing Sciences, University of Aberdeen, Aberdeen, Scotland; July 15, 2009.
9. "Basin of coexistence," Planery talk, International Conference on Dynamics in Systems Biology, University of Aberdeen, Aberdeen, Scotland; September 17, 2009.
10. "Predicting complex networks based on time series," Opening Planery talk, Dynamics Days Workshop, National Chiao Tong University, Hsin Chu, Taiwan; January 12, 2010.
11. "Evolutionary-game approach to species coexistence," Closing Planery talk, Dynamics Days Workshop, National Chiao Tong University, Hsin Chu, Taiwan; January 12, 2010.

## 6 Past Honors

1. Air Force PECASE, 1997.
2. Election as a Fellow of the American Physical Society, 1999. Citation: *For his many contributions to the fundamentals of nonlinear dynamics and chaos*.
3. Outstanding Referee Award, American Physical Society, 2008.

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**14. ABSTRACT**

The main goal of the project was to conduct a comprehensive study of complex networks from the perspectives of security and information protection using an interdisciplinary approach. Specific Objectives were: (1) cascading breakdown of complex networks triggered by attacks and control strategies; (2) security of complex clustered networks and gradient networks; (3) attack-induced oscillations of complex networks and control strategies; (4) security and robustness of wireless sensor networks; (5) optimization of synchronization in complex networks; (6) dynamics-based network scalability; (7) spreading processes on complex networks; (8) searching for universal dynamics on complex networks; and (9) time-series based prediction of hub nodes and network topology. The outcomes of the project include 25 papers published or accepted by refereed journals. One Ph.D. student graduated with a thesis entitled "Dynamics and Security of Complex Clustered Networked Systems" and received the Palais Outstanding Doctoral Student Award for 2008-2009 from ASU's School of Electrical, Computer and Energy Engineering. During the project period, the PI gave 11 invited talks on topics derived directly from the AFOSR project. Collaboration started with Dr. Vassilios Kovanis from AFRL at Wright Patterson AFB on complex dynamical systems and compressive sensing.

**15. SUBJECT TERMS**
Complex Networks, Network Security, Cascading Breakdown, Synchronization, Scalability, Universal Dynamics, Spreading Dynamics, Wireless Sensor Networks, Time-Series Analysis, Network Prediction

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